Modeling Social Dynamics in Cyber-Physical-Social Classroom Systems

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ABSTRACT

In this paper, we present an agent-based model (ABM) to study equitable interventions in cyber-physical-social systems (CPSIS) within educational environments. With the use of influence derived from physical and cognitive factors, we can capture the nuances of social interactions and peer learning. Simulation results demonstrate how different layouts and instructional strategies impact equity, providing valuable insights for educators aiming to optimize classroom environments for diverse learners. The model represents an explainable framework for participatory modeling and intervention design.

CCS CONCEPTS

• **Human-centered computing → Social network analysis**; **Participatory design**; • **Computing methodologies → Modeling methodologies**; **Multiscale systems**; • **Computer systems organization → Embedded and cyber-physical systems**;

KEYWORDS

Agent-based Modeling, Equity Metrics, Social Learning

ACM Reference Format:
Tyler James Nanoff and Hugo Gonzalez Villasanti. 2024. Modeling Social Dynamics in Cyber-Physical-Social Classroom Systems. In *The 11th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys '24), November 7–8, 2024, Hangzhou, China.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3671127.3699528

1 INTRODUCTION

1.1 Modeling Education Processes

Classroom environments are dynamic spaces where student interactions, physical layouts, and instructional strategies significantly influence learning outcomes. However, promoting equitable learning experiences, particularly for neurodivergent students, remains a challenge [4]. Understanding and managing peer skill resource allocation is essential for young learners' social and cognitive growth [3], making education equity a crucial goal [14]. We introduce a digital twin model that captures these complex interactions, enabling educators to explore and optimize learning environments in real-time. Recent studies highlight the critical role of teachers in managing classroom social dynamics to support special education [8], and the importance of peer effects in influencing language growth in preschool classrooms [5]. Moreover, technological interventions, such as classroom behavioral imaging, have been explored to enhance early childhood inclusion planning [21].

Vygotsky's Zone of Proximal Development provides a foundational understanding of how peer interactions can facilitate learning [28]. Social learning theories that highlight the role of peer influence in cognitive development [25]. Agent-based modeling (ABM) provides a powerful tool to encode such theories and simulate classroom interactions, where each agent represents a student or teacher. Recent studies using ABM have demonstrated the potential of technology-enabled peer-mediated interventions to improve social and language outcomes for socially isolated preschoolers [10]. Modeling human behavior in cyber-physical-social infrastructure systems has shown the importance of considering complex interactions in such environments [6]. In addition to modeling social interactions, physical classroom environments significantly impact student behavior and learning outcomes. The spatial configuration of classrooms influences not only how students interact socially but also their cognitive engagement with the learning process. Research by Fouad [11] emphasizes the relationship between spatial design and learning, illustrating how adaptable physical spaces enhance socialization and academic performance. Similarly, the design and organization of learning spaces have been shown to influence how students interact and learn within educational environments [30]. These findings suggest that incorporating spatial factors into ABM simulations can lead to more accurate models of classroom dynamics and improve the efficacy of educational interventions. Additionally, teacher management of classroom social dynamics plays a crucial role in fostering student adjustment and interaction. Gest et al. [15] discuss how teacher interventions can influence social dynamics, impacting both academic and social outcomes for students.

Recent advances in classroom sensing technologies provide promising tools to model learning dynamics and enhance classroom interventions for equitable learning. These technologies offer a non-intrusive way to monitor student interactions, cognitive engagement, and physical activity within the learning environment. Ogan [26] proposes a shift from device-based sensing toward off-device approaches, such as classroom-embedded sensors that allow students the freedom to move without being tethered to technology. These sensors can capture essential information about student behaviors, such as body movements, facial expressions, and peer interactions, enabling real-time feedback for educators to adjust their

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ACM ISBN 979-8-4007-0706-3/24/11
https://doi.org/10.1145/3671127.3699528

teaching strategies. Foster [9] emphasizes the role of multi-modal classroom sensing in understanding student engagement.

1.2 System Design in Education

Design principles play a crucial role in creating educational environments that support diverse learning needs. Banathy [1] emphasizes viewing educational environments as complex systems where physical, cognitive, and social interactions occur simultaneously. Furthermore, the design of classroom layouts has been shown to significantly impact student interactions and learning outcomes [18]. Observations of children's interactions across different classroom activity settings highlight the importance of physical and social environments in shaping learning experiences [2].

Designing educational technology involves understanding how physical, cognitive, and digital elements interact to shape learning outcomes. Research by Worsley and Blikstein has shown the importance of integrating adaptive systems that can differentiate between student learning strategies in real-time using multi-modal learning analytics (MMLA). These systems track multiple data streams, such as gesture, speech, and interaction patterns, to adjust instructional interventions dynamically, allowing for personalized feedback with aims to improve learning outcomes [34]. Similarly, instructional support systems in inquiry-based learning environments have demonstrated their ability to provide effective, continuous, and context-specific feedback [20]. Sensing technologies that track student behavior and engagement provide a greater ability to understand and act upon systems [26]

Equity in education technology requires systems that adapt to the needs of all learners, ensuring that interventions do not inadvertently perpetuate inequities. Siddiqi and Heydari [29] discuss the importance of incorporating equity and fairness norms into sociotechnical systems. The principles from Value Sensitive Design [13] call for prioritizing human values such as autonomy and fairness in the design of intelligent systems. Similarly, participatory design emphasizes involving stakeholders in system development, enhancing user agency [32]. Grogan [17] emphasizes the importance of co-design and co-simulation in engineering systems, where involving stakeholders early in the process leads to more robust and adaptable designs.

1.3 Research Objectives

The primary goal of this research is to develop a computational model to inform the design of instructional strategies, classroom configurations, and interventions. Our approach builds upon peer effect models such as the Friedkin-Johnsen framework [12] and Social Interdependence Theory [23], which emphasize the importance of cooperative learning and positive interdependence among students. The objectives of this research are as follows:

- **Model the classroom dynamics:** develop a model that captures the learning dynamics and its association with the social and physical classroom environment. This model will be estimated with sensor data streams to simulate how instructional strategies and classroom layouts affect learning outcomes.
- **Formulate a design cost function:** based on key metrics such as equity, engagement, and learning outcomes, which will be developed with the help of stakeholders. This cost function will allow us to optimize instructional strategies and classroom configurations, ensuring that the classroom environment is adaptive to the needs of all students, especially those who are traditionally under-served.
- Explore design configurations: We will test the proposed model and cost function in simulated classroom environments. The results will include evaluations of how the physical layout impacts instructional efficiency, student engagement, and equity, demonstrating the potential for adaptive interventions to improve learning outcomes.

2 SYSTEM DESIGN AND IMPLEMENTATION

2.1 Classroom Environment Modeling

We consider two classroom layouts using potential fields, a method commonly applied to simulate human behavior, such as navigation and obstacle avoidance, due to its ability to capture both attractive and repulsive forces that guide movement toward goals and away from obstacles [7, 19]. Attractors in our model represent areas of interest for children, while repulsers mark zones to avoid. Hard boundaries simulate immovable objects like tables or cubbies. Each layout is represented on a 3D grid with X and Y coordinates corresponding to classroom space, and Z-values indicating the intensity of attractors, repulsers, and barriers.

2.1.1 Layout 1 - properly designed floor plan. : Layout 1 was chosen to simulate an interactive classroom environment with various zones serving as attractors, encouraging students to engage in specific activities or materials. This layout was sourced from [16], who explained the top preschool classroom layouts and daycare floor plans. As illustrated in Figure 1, the properly-designed layout includes various zones:

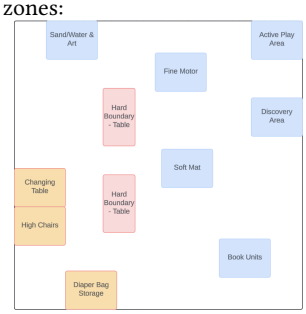


Figure 1: Properly-designed layout. Adapted from [16].

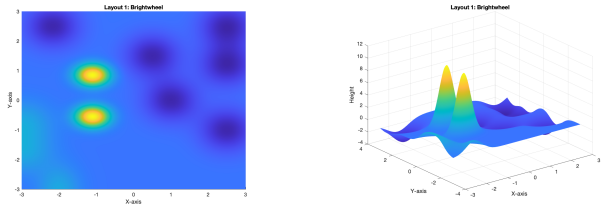
Based on the layouts, a surface map contour was created to represent the classroom. This was done by using the following equation:

$$Z(x,y) = k_h \cdot e^{-\left(\frac{(x-x_c)^2}{x_w} + \frac{(y-y_c)^2}{y_w}\right)} \quad (1)$$

The k_h (height) parameter controls the strength of attraction or repulsion a feature exerts on the potential field. Attractors (e.g., pulling towards a reading nook) have negative heights, while repulsers (e.g., pushing away from noisy areas) have positive heights. Similar to Khatib's [24] potential fields, we use height to directly quantify the intensity of these forces, which could be measured by observing how much time children spend near or avoiding certain

areas. This makes it easier to adjust their influence in the classroom and, in the future, potentially vary the influence that certain features have on certain children. The (x_c, y_c) (x and y centers) parameters represent the center coordinates of a feature, such as a desk or play area, based on its real-world location. These can be measured using classroom layouts or object positioning. Each feature has a unique center, and the potential field's peak (or dip) occurs at this center. The (x_w, y_w) (widths) parameters determine how far a feature's influence extends in the x and y directions. Wider ranges could reflect how far children are affected by features like noise or a play zone, which can be measured by tracking movement patterns in the classroom. For example, a repulser with a large width might represent a noisy area that affects students across a significant portion of the classroom.

Features were added by changing the x and y widths and centers, as well as the heights. Attractors represented features with a height of -3, repulsers represented features with a height of +2, and hard boundaries represented features with a height of +10. Each feature's influence is directly related to how it interacts with the physical space and environment, making these parameters realistic to measure and adjust in a classroom setting. This framework allows the easy addition and removal of features inside a classroom. Using this framework allowed the following map to be created for the layout in Figure 2:



(a) Layout 1 Surface 2D **(b) Layout 1 Surface 3D**

Figure 2: Surface Contours for Layout 1

2.1.2 Layout 2 - poorly designed floor plan. : Layout 2 represents a poorly designed classroom that does not consider children's developmental needs. This layout was developed with insights from [22], which described the following issues with some preschool classrooms: *Clustered and Isolated Activity Zones:* A classroom might cluster all high-energy activities (like play areas) on one side and place low-energy areas like reading zones far away. This leads to over-stimulation in some areas and under-utilization in others, breaking the interaction flow. *Repulsive Elements in Pathways:* Placing large furniture like tables or book units in the middle of high-traffic areas creates barriers, limiting children's ability to move freely between zones. *Missing Clear Literacy Areas:* A lack of well-defined literacy zones (e.g., no designated reading corner) reduces children's access to and engagement with books, negatively impacting literacy learning. The key features here include: Attractors: Rowdy Play Area. Repulsers: Collegiate Level Textbooks, which discourage engagement. Hard Boundaries: Storage shelving that restricts movement across the room.

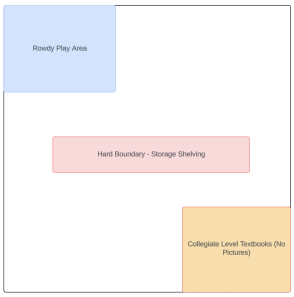


Figure 3: Poorly-designed layout.

Each layout is assigned a set of reference signals representing the teacher's intended locations for students during different times of the day. These signals direct students between various centers and are used to model real-world classroom traditions (i.e., center time, where students are transitioning from one activity to the next). Layout 1 guides students sequentially from Book Units to Sand/Water, and so forth. Layout 2 transitions students from the attractive area to the repulsive area, and then incorporates random spots reflecting a less structured and planned out environment. Each layout includes at least one of both the attractive and repulsive reference spots.

2.2 Agent-Based Modeling

Our agent-based model captures the interactions between students and teachers, incorporating influence weights based on physical and cognitive proximities. The influence weights are dynamic, evolving over time to reflect changes in classroom dynamics. In our agent-based modeling approach, we capture the interactions between students and teachers, incorporating influence weights based on both physical proximities (proximal factors that are updated each second) and cognitive state (distal factors that are updated each day). A "day" in the classroom is represented as a 2-hour span of center time, which is known as the time when teachers are transitioning students from activity to activity. This dynamic modeling helps simulate the complex and evolving nature of student interactions within different classroom layouts.

2.2.1 Proximal (Position Update). : The position update represents the physical state of each student as they move within the classroom grid over time. This update is modeled as a function of their current position, the influence of the classroom environment, guidance from the teacher, and interactions with peers. The model operates on discrete time steps but considers the movement as continuous within each interval, effectively capturing real-time student behavior.

The position of student i at time t, with t set to one second, is denoted as $x_i(t) \in \mathbb{R}^2$, representing their location within the classroom grid. The 1-second time step was chosen because it reflects the typical pace of student movements, capturing meaningful changes. Shorter intervals would add unnecessary complexity while still allowing for efficient, real-time behavior modeling. The position update follows the equation:

$$x_i(t+1) = x_i(t) + v_i(t)\Delta t$$

where $v_i(t)$ is the velocity of individual i, and Δt is the discrete time step, set to 1 second. The velocity is defined as:

$$v_i(t) = -\eta \left(\nabla \phi_i^g(x_i(t)) + \nabla \phi_i^c(x_i(t)) + \nabla \phi_i^p(x_i(t)) \right)$$

This equation incorporates three key influences on each student's movement:

- ϕ_i^g (Classroom Layout): Impact of the physical layout, including attractors and repulsers. It is derived from the gradient of the potential surface Z, directing students toward lower-cost (attractive) areas.
- ϕ_i^c (Teacher Influence): is derived from the teacher's control, guiding students toward a sequence of target reference points. The teacher's control is represented by a reference signal $r_i(t)$, which guides students to specific target locations throughout the day. The detailed parameter choices for the reference signals allow the capture of structured versus less structured teaching scenarios.
- ϕ_i^p (Peer Influence): incorporates social interaction, capturing the influence of peers based on their relative positions and cognitive states. This is determined by the influence weights that agents have on each other. A cognitive similarity and close distance to one another will have a higher influence on the student than a large cognitive difference and far distance would. This is consistent with the interplay between homophily-based appraisal dynamics and influence-based opinion dynamics dynamics presented by Liu [25]

Substituting $v_i(t)$ into the position update equation gives:

$$x_i(t+1) = x_i(t) - \eta \left(\nabla \phi_i^g(x_i(t)) + \nabla \phi_i^c(x_i(t)) + \nabla \phi_i^p(x_i(t)) \right)$$

The velocity $v_i(t)$ is thus determined by the combined gradients of these factors, guiding student movement across the classroom surface, modeled as a surface map $Z(x)$.

2.2.2 Formulation of potential functions ϕ^g, ϕ^c, and ϕ^p.

- Influence of the Physical Classroom Layout (ϕ^g):
  - Potential Function, where $Z(x)$ is the height map:
    $$\phi_i^g(x_i(t)) = Z(x_i(t))$$
  - Gradient:
    $$\nabla \phi_i^g(x_i(t)) = \frac{2}{x_w} k_h^i \left(x_i(t) - x_c\right) e^{-\left(\frac{(x_i(t)-x_c)^2}{x_w}\right)}$$
- Influence of the Teacher's Control (ϕ^c):
  - Potential Function, where $r_i(t)$ is the teacher's reference point:
    $$\phi_i^c(x_i(t)) = \frac{1}{2} k_i^c \left(x_i(t) - r_i(t)\right)^2$$
  - Gradient:
    $$\nabla \phi_i^c(x_i(t)) = k_i^c (x_i(t) - r_i(t))$$
- Influence of Peers (ϕ^p):
  - Potential Function, where w_{ij} represents the peer influence weight. Social Interdependence Theory (SIT) was used to come up with the physical proximity portion of this equation [23], which emphasizes that positive interdependence and frequent collaboration occurs most naturally among students who are close to each other.
    $$\phi_i^p(x_i(t)) = -k_i^p \sum_{j \neq i} w_{ij} \cdot \left(x_i(t) - x_j(t)\right)^2$$
  - Gradient:
    $$\nabla \phi_i^p(x_i(t)) = -k_i^p \sum_{j \neq i} w_{ij} \cdot \left(x_j(t) - x_i(t)\right)$$
- Overall Position Update:

$$\begin{aligned} x_i(t+1) = x_i(t) - \eta \Bigg(& \frac{2}{x_w} k_h^i (x_i(t) - x_c) e^{-\left(\frac{(x-x_c)^2}{x_w}\right)} \\ & + k_i^c \cdot (x_i(t) - r_i(t)) \\ & + \left(-k_i^p \sum_{j \neq i} w_{ij} \cdot \left(x_j(t) - x_i(t)\right) \right) \Bigg) \end{aligned} \tag{2}$$

2.2.3 Distal (Cognitive State Update). The cognitive state update is used to capture how each student's cognitive abilities evolve over time. These are influenced by their interactions with peers, teachers, and the activity centers around the classroom. This component operates on a different timescale than the proximal portion; here, it operates on a "per day" basis, where one day represents 2 hours (i.e., 7200 seconds) of the proximal update. This is done because the actual time students spend in "center time" during the day is usually around 2 hours long [33]. As such, the time step here to represent a day is denoted as τ to differentiate it from the time step in the proximal portion of the model.

The cognitive state $c_i(\tau + 1)$ for student i on day τ is updated as follows:

$$c_i(\tau + 1) = \gamma_i c_i(\tau) + I_i(\tau) \tag{3}$$

Where:

- $\gamma_i \in [0, 1]$: Represents the retention factor of student i. This indicates their ability to retain learned information from the previous day.
- $I_i(\tau)$: Total influence on student i during day τ, composed of social, center, and teacher influences.

The total influence $I_i(\tau)$ is given by:

$$I_i(\tau) = \alpha_i I_{i,\text{social}}(\tau) + \beta_i I_{i,\text{center}}(\tau) + \zeta_i I_{i,\text{teacher}}(\tau) \tag{4}$$

Here, α_i, β_i, and ζ_i are positive constants that represent the sensitivity that student i has to each type of influence.

1. Peer Influence $I_{i,peer}(\tau)$. The peer influence term determines how much influence interactions with other students have on the cognitive state of the student i.

$$I_{i,\text{peer}}(\tau) = \sum_{j \neq i} \tilde{d}_{ij}(\tau) g_p \left(c_j(\tau) - c_i(\tau)\right) \tag{5}$$

Where:

- $\tilde{d}_{ij}(\tau)$: The normalized physical proximity between students i and j at time τ.

- $g_p(\Delta c)$: The cognitive distance function, formulate with

$$g_p(x) = \begin{cases} ax^2, & \text{if } x >= 0. \\ bx^2, & \text{otherwise.} \end{cases} \quad (6)$$

Here, a, b are constants representing the influence slope when the cognitive differences are positive or negative, respectively.

2. Center Influence $I_{i,center}(\tau)$. The center influence represents the impact of shared learning resources or group activities at specific activity centers in the classroom:

$$I_{i,\text{center}}(\tau) = \tilde{d}_{iC}(\tau) g_c(c_C(\tau) - c_i(\tau)) \quad (7)$$

Where:

- $\tilde{d}_{iC}(\tau)$: The normalized distance between student i and center C.
- $g_c(x)$: is the cognitive influence provided by the center, parameterized as in Equation 6.

3. Teacher Influence $I_{i,teacher}(\tau)$. The teacher's influence is modeled similarly:

$$I_{i,\text{teacher}}(\tau) = \tilde{d}_{iT}(\tau) g_T(c_T(\tau) - c_i(\tau)) \quad (8)$$

- $\tilde{d}_{iT}(\tau)$: The normalized distance between student i and the teacher.
- $g_T(x)$: is the cognitive influence provided by the teacher, parameterized as in Equation 6.

The final cognitive state update is then formulated as:

$$c_i(\tau+1) = \gamma_i c_i(\tau) + \alpha_i I_{i,\text{social}}(\tau) + \beta_i I_{i,\text{center}}(\tau) + \zeta_i I_{i,\text{teacher}}(\tau) \quad (9)$$

Justice Scores for Evaluating Equity. We evaluate how equitable a learning environment is using the predicted cognitive state evolution via four justice scores. We use a Rawlsian distributive justice approach to operationalize equity in allocating resources in preschool classrooms. Our equity scores provide insights into the learning environment's equity at any time in the simulation. With these scores, designers can evaluate different interventions, providing insights into effective teaching strategies and classroom design.

- J1 is an Average-Based Justice Score that takes the average cognitive state across all students, reflecting overall learning progress:

$$J1(\tau) = \frac{1}{N} \sum_{i=1}^{N} c_i(\tau)$$

- J2 is an Extremum-Based Justice Score (Minimum Input) that captures the cognitive state of the least advanced student, indicating how well the system supports the most challenged student:

$$J2(\tau) = \min(c_1(\tau), c_2(\tau), ..., c_N(\tau))$$

- J3 is a Gini Coefficient-Based Justice Score that measures inequality among students' cognitive states. A higher $J3$ means more equality, while a lower $J3$ suggests significant disparities:

$$J3(\tau) = 1 - \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} |c_i(\tau) - c_j(\tau)|}{2N^2 \sum_{i=1}^{N} c_i(\tau)}$$

- J4 is a Normalized Extremum-Based Justice Score that normalizes the difference between the lowest and highest cognitive states, ensuring that improvements in the least advanced student are fairly weighed against those of the most advanced:

$$J4(\tau) = \frac{\min(c_1(\tau), c_2(\tau), ..., c_N(\tau))}{\max(c_1(\tau), c_2(\tau), ..., c_N(\tau))}$$

3 RESULTS AND DISCUSSION

3.1 Simulation Setup

In this section, we detail the simulation parameters and testing scenarios used to evaluate the classroom across two different layouts. The goal was to observe how these designs influence student movement, cognitive development, and overall equity as measured by the Justice Scores over a 5-day period, with each day consisting of 2 hours (7200 seconds) of activity. The model's position updates use 1-second time steps, accounting for movement influenced by the layout's surface gradient ($k_f = 0.05$), teacher guidance towards target points ($k_c = 0.01$), and peer interaction based on proximity and cognitive similarity ($k_p = 0.01$). The adjustment rate ($\eta = 0.1$) manages how quickly students reposition, while the maximum step size (0.005) ensures realistic movement limits per time step. For the cognitive state updates, retention values (γ) range from 0.9 to 0.99, reflecting the ability to retain learned information. The influence of peer learning, centers, and teacher guidance is captured using constants α_i, β_i, and ζ_i, each initially set to 2, 1, and 1.5, respectively, to simulate sensitivity to these interactions. Additionally, damping (damping = 0.1) is applied to smooth student movement. These parameters are currently set as initial estimates; further refinement, including parameter estimation using real classroom data, will be conducted to enhance the model's accuracy. This is similar to how models in other fields, like mood dynamics or opinion formation, employ differential equations with estimated parameters based on observed data, our model will evolve as we gather real-time classroom data.

Studies like [25] and [31] demonstrate the effectiveness of refining model parameters using real-world observations, sensor data, and participatory design input. By incorporating real-time data from neurodivergent and neurotypical students, we aim to make our model reflective of actual classroom interactions. This approach is similar to [27], who highlights the importance of adapting models based on longitudinal data to better capture evolving social dynamics. Processes like these will assist in transforming the model from an exploratory tool into a more precise instructional support system capable of responding to the unique social learning dynamics present in each classroom.

Test Scenarios and Data Collection: The simulation recorded student paths for the first day, showing how the layout's attractors, repulsers, and hard boundaries affected movement. Each student's cognitive state was tracked over the 5-day period, visualizing growth influenced by peer interactions, teacher guidance, and the physical classroom environment. Four justice scores (J1 to J4) were calculated daily to measure equity across students' cognitive states, allowing us to compare the effectiveness of each layout in promoting fair learning outcomes.

3.2 Results

3.2.1 Day 1 Movement Paths: The movement paths showed significant differences in how students engaged with their environments. In Layout 1, there was diverse movement, suggesting multiple areas encouraged exploration and interaction. In contrast, Layout 2 (Poorly Designed) had more concentrated paths, suggesting limited stimulation and movement, which contributed to lower justice scores.

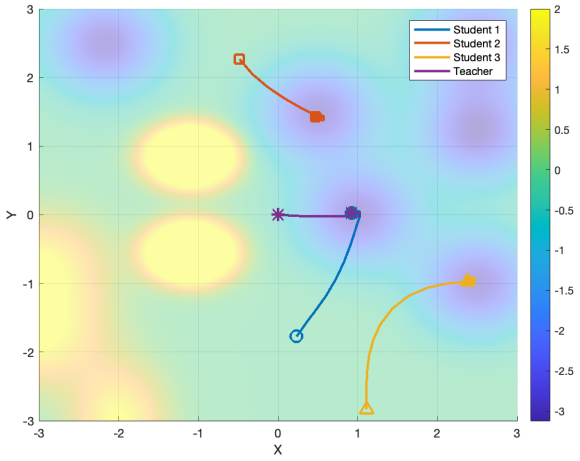


Figure 4: Day 1 Movement Paths for Layout 1

3.2.2 Cognitive Scores Over Time: Cognitive state progression varied by layout. Layout 1 showed consistent and comparatively equitable growth among students. On the other hand, Layout 2 highlighted disparity, with some students advancing significantly more than others.

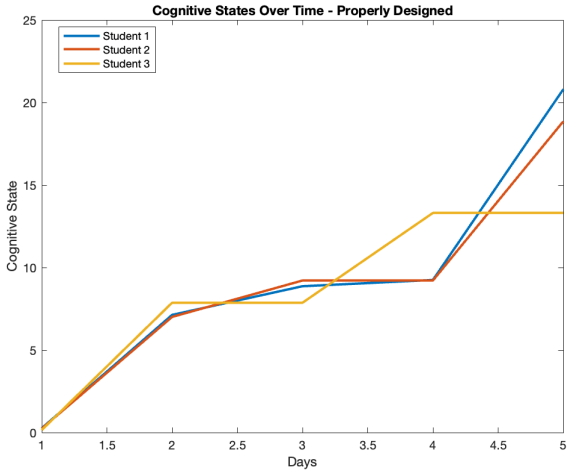


Figure 5: Cognitive States Over Time for Layout 1

The figure below shows the J4 (normalized extremum-based justice score) comparison across both layouts.

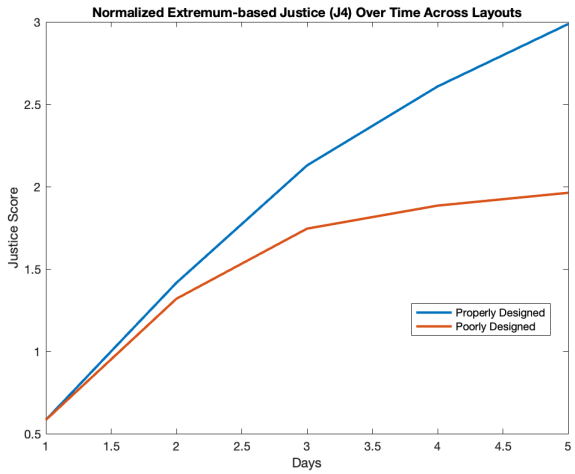


Figure 6: Normalized extremum-based Justice score (J4) over time across layouts

These results indicate that thoughtful classroom design significantly influences student equity and cognitive growth, underscoring the importance of well-planned layouts for effective educational outcomes.

4 CONCLUSION AND FUTURE WORK

4.1 Summary of Contributions

This paper presents an introductory agent-based modeling framework that integrates physical classroom layouts, peer interactions, and instructional strategies, with the goal to simulate and analyze the cognitive dynamics of preschool educational environments. This model utilized potential fields to represent attractors, repulsers, and barriers, which allowed the simulation of how students physically and cognitively navigate within different classroom layouts. We formulated a set of justice scores based on Rawlsian distributive justice principles to be able to quantitatively evaluate equity in the different classroom layouts. Through the simulation of the various layouts, our preliminary results demonstrate the impact of thoughtful well-planned physical spaces in classroom design and instructional strategies.

4.2 Limitations

The current model is built and tested with simulated data, using preliminary parameters that have been intuitively chosen, but not yet calibrated with real world classroom data. The model also makes several simplifications and assumptions that may not hold true in a real classroom setting such as the homogeneous retention factors and influence sensitivities across the students. The model does not account for external factors like parent instruction and home-life, socio-economic status, language barriers, and cultural differences, all of which have the potential to impact learning outcomes and

equity. The justice scores that were formulated to assess equity were based on theoretical constructs, and may not properly capture the many dimensions of equity that are relevant to students, educators, parents, and policymakers. As of now the model only includes three students and one teacher, which is a smaller representation of preschool classrooms compared to typical classrooms that usually have preferred teacher to student ratios ranging from 1:6 to 1:12. All of these ideas and metrics will require iteration, adaptation, and future participatory design along with real-world data to help bring the model closer to consistently modeling the reality that students face in the preschool classroom.

4.3 Future Directions

Building upon this introductory model, future work will involve incorporating real-time sensor data to capture the implementation and testing of the system in live classroom settings. We intend to collaborate with students, teachers, parents and other educational stakeholders through the use of participatory design, ensuring that the model captures the realities that the students and teachers feel they face on a daily basis, and is also adaptable to the specific educational needs of each student. This collaboration will serve to facilitate the development of a cyber-physical-social infrastructure system (CPSIS) that aims to support autonomy and equity for underserved and neurodivergent students. This CPSIS will serve as a digital twin, enabling real-time data capture and the simulation of different instructional strategies and classroom layouts, providing tailored, data-driven recommendations for educators.

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Received 20 September 2024; revised 12 March 2009; accepted 5 June 2009